This talk will describe a new class of methods for estimating a low-rank matrix from a noisy observed matrix, where the error is measured by a type of weighted loss function. Such loss functions arise naturally in a variety of problems, such as submatrix denoising, filtering heteroscedastic noise, and estimation with missing data. We introduce a family of spectral denoisers, which preserve the left and right singular subspaces of the observed matrix. Using new asymptotic results on the spiked covariance model in high dimensions, we derive the optimal spectral denoiser for weighted loss. We demonstrate the behavior of our method through numerical simulations.